Anti-Entropy Bandits for Geo-Replicated Consistency

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ABSTRACT

Eventually consistent systems can be made more consistent by reducing the time until a write is fully replicated, improving their visibility. While gossip-based anti-entropy methods scale well, random selection of anti-entropy partners is less than efficient. We propose an improvement to pairwise, bilateral anti-entropy; instead of uniform random selection, we introduce reinforcement learning mechanisms to assign selection probabilities to replicas most likely to have information. The result is more efficient replication, faster visibility, and higher consistency, while maintaining high availability and partition tolerance.

CCS CONCEPTS

• **Computing methodologies → Reinforcement learning**; • **Computer systems organization → Fault-tolerant network topologies**; *Reliability*; *Availability*;

KEYWORDS

Eventual Consistency, Anti-Entropy, Geo-Replication, Multi-Armed Bandits

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INTRODUCTION

A distributed system is made highly available when individual servers are allowed to operate independently, which can be prone to failure and high latency PJK: Why?. The independent nature of the server's behavior means that it can immediately respond to client requests, but that it does so from a limited, local perspective which may be inconsistent with another server's response. If individual servers in a system were allowed to remain wholly independent, individual requests from clients to different servers would create a lack of order or predictability, a gradual decline into inconsistency, e.g. the system would experience *entropy*. To combat the effect of entropy while still remaining highly available, servers engage in periodic background *anti-entropy sessions* [10].

Anti-entropy sessions synchronize the state between servers ensuring that, at least briefly, the local state is consistent with a portion of the global state of the system. If all servers engage in anti-entropy sessions, the system is able to make some reasonable guarantees about the timeliness of responses; the most famous of which is that without requests the system will become consistent, eventually. More specifically, inconsistencies in the form of stale reads can be bound by likelihoods that are informed by the latency of anti-entropy sessions and the size of the system [2]. Said another way, overall consistency is improved in an eventually consistent system by decreasing the likelihood of a stale read, which is tuned by improving the *visibility latency* of a write, the speed at which a write is propagated to a significant portion of servers. This idea has led many system designers to decide that eventual consistency is "consistent enough" [3, 11], particularly in a data center context where visibility latency is far below the rate of client requests, leading to practically strong consistency.

Recently there have been two important changes in considerations for the design of such systems that have led us to re-evaluate propagation speed: systems are growing and becoming geographically distributed outside of the datacenter. Scaling an eventually consistent system to dozens or even hundreds of nodes increases the radius of the network, which leads to increased noise during anti-entropy; e.g. the possibility that an anti-entropy session will be between two already synchronized nodes. Geographic distribution and extra-datacenter networks increase the latency of anti-entropy sessions so that inconsistencies become more apparent. Large, geographically-distributed systems are becoming the norm – from content delivery systems that span the globe, to mobile applications, to future systems such as automated vehicular networks, and all will require additional consistency guarantees without sacrificing availability.

We propose a new class of adaptive distributed data systems whose replicas monitor their environment and modify their behavior to optimize consistency. Anti-entropy uses gossip and rumor spreading to efficiently propagate updates deterministically without saturating the network [5, 6, 9]. These protocols use uniform random selection to choose synchronization peers, which means that a write occurring at one replica is not efficiently propagated across the network. We propose the use of *multi-armed bandit* algorithms [7, 8] to optimize for fast, successful synchronizations by modifying peer selection probabilities. The result is a synchronization topology that emerges according to access patterns and network latency, often localizing communicating replicas to produce efficient synchronization, lower visibility latency, and increased consistency.

SYSTEM DESCRIPTION

Our system implements an eventually consistent, in-memory key-value store that is totally replicated using anti-entropy [4]; a brief sketch of our implementation follows.

Accesses and Consistency

Clients can `Put` (write) and `Get` (read) key-value pairs to one or more replicas in a single operation. The set of replicas that responds to a client creates a quorum that must agree on the state of the operation at its conclusion. Clients can vary read and write quorum sizes to

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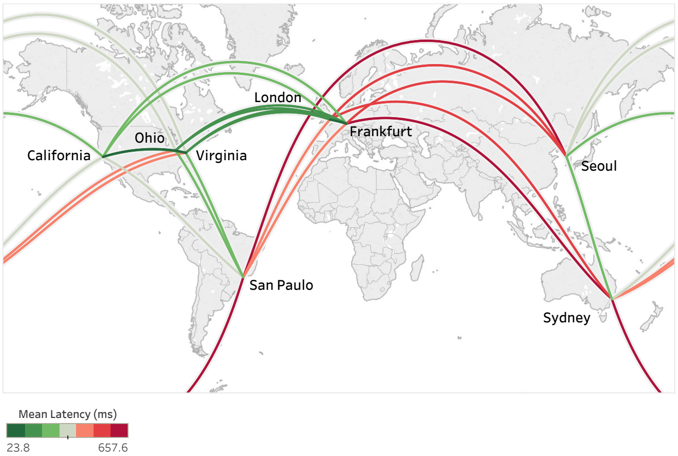

Figure 1: Latencies in a geo-replicated key-value store

improve consistency or availability – larger quorums reduce the likelihood of stale reads but smaller quorums respond much more quickly. In large, geo-replicated systems we assume that clients will prefer to choose fewer, local replicas to connect with, optimistic that collisions across the wide-area are rare, e.g. that writes are localized but reads are global.

On `Put`, the instance of the key-value pair is assigned a monotonically increasing, conflict-free *version number* [1]. For simplicity, we assume a fixed number of replicas, therefore each version is made up of two components: the *update* and *precedence ids*. Precedence ids are assigned to replicas during configuration, and update ids are incremented to the largest observed value during synchronization. As a result, any two versions generated on `Put` are comparable such that the *latest* version of the key-value pair is the version with the largest update id, and in the case of ties, the largest precedence id.

Additional version metadata, including the parent version, ~~that object was created from~~, implements a virtual object history that allows us to reason about consistency. Keys can be managed independently, e.g. each key has its own update id sequence, or all objects can be managed together with a single sequence; in the latter case, one can construct an ordering history of operations to all objects.

There are two primary inconsistencies that can occur in this system: *stale reads* and *forked writes*. A stale read means that the `Get` operation has not returned the globally most recent version of the object. A forked write, on the other hand, means that there are two branches of the object history, created by concurrent writes to the same object. As we will see in the next section, one of these writes will be *stomped* before it can become fully replicated. The ideal consistency for a system is represented by a linear object history without forks.

Anti-Entropy

Anti-entropy sessions are conducted in a pairwise fashion at a routine interval to ensure that the network is not saturated with synchronization requests. There are two basic forms of synchronization: *push* synchronization is a fire-and-forget form of synchronization where the remote is sent the latest version of all objects, whereas *pull* synchronization requests the latest version of objects and minimizes the size of data transfer. We have implemented *bilateral* synchronization which combines push and pull in a two-phase exchange.

Bilateral anti-entropy starts with the initiating replica sending a vector of the latest local versions of all keys currently stored (this can be optimized with Merkel trees to make comparisons faster). The remote replica compares the versions sent by the initiating replica with its current state and responds with any objects whose version is *later* than the initiating replica's as well as another version vector of requested objects that are earlier on the remote. The initiating remote then replies with the requested objects, completing the synchronization. We refer to the first stage of requesting later objects from the remote as the pull phase, and the second stage of responding to the remote the push phase.

There are two important things to note about this form of synchronization. First, this type of synchronization implements a *latest writer wins* policy. This means that not all versions are guaranteed to become fully replicated – if a later version is written during propagation of an earlier version, then the earlier version gets stomped by the later version. If there are two concurrent writes, only one write will become fully replicated. Second, the visibility latency is maximized when all replicas choose a remote synchronization partner that does not yet have the update. This means that maximal visibility latency is equal to $t \log_3 n$, where t is the anti-entropy interval and n is the number of replicas in the network. However, because of stomps and noise created by uniform random selection of synchronization partners, this latency is never practically achieved.

BANDIT APPROACHES

Often used in active and reinforcement machine learning, multi-armed bandits refer to a statistical optimization procedure that is designed to find the optimal payout of several choices that each have different probabilities of reward. A bandit problem is designed by identifying several "arms", so called because multi-armed bandit refers to pulling slot machine arms, as well as a reward function that determines how successful the selection of an arm is. During operation, the bandit uses a *strategy* to select an arm – the most common of which is epsilon greedy – then updates the rewards of the selected arm, normalized by the number of selections. The arm with the highest reward value is considered the optimal arm.

Bandits must balance exploration of new arms with possibly better reward values and exploitation of an arm that has higher rewards than the other. In the epsilon greedy strategy, the bandit will select the arm with the best reward with some probability $1 - \epsilon$, otherwise it will select any of the arms with uniform probability. The smaller ϵ is, the more the bandit favors exploitation of known good arms, the larger ϵ is, the more it favors exploration. If $\epsilon = 1$ then the algorithm is just uniform random selection. A simple extension of this is annealing epsilon greedy, which starts with a large ϵ, then as the number of trials increases, steadily decreases ϵ on a logarithmic scale.

	Pull	**Push**	**Total**
Synchronize at least 1 object	0.25	0.25	0.50
Synchronize multiple objects	0.05	0.05	0.10
Latency <= 5ms (local)	0.10	0.10	0.20
Latency <= 100ms (regional)	0.10	0.10	0.20
Total	*0.50*	*0.50*	*1.00*

Table 1: Reward Function

Peer selection for anti-entropy is usually conducted with uniform random selection. To extend anti-entropy with bandits, we design a selection method whose arms are remote peers and whose rewards are determined by the success of synchronization. The goal of adding bandits to anti-entropy is to optimize selection of peers such that the visibility latency becomes closer to the optimal propagation time as a synchronization topology emerges from the bandits. A secondary goal is to minimize anti-entropy latency by preferring local (in the same data center) and regional (e.g. on the same continent) connections.

Our reward function favors synchronizations to replicas where the most writes are occurring by giving higher rewards to anti-entropy sessions that exchange later versions in either a push or a pull as well as additional rewards if more than one object is exchanged. Additionally, the latency of the synchronization RPC is computed to reward replicas that are near each other. The complete reward function is given in Table 1: for each phase of synchronization (push and pull), compute the reward as the sum of the propositions given. For example if a synchronization results in 3 objects being pulled in 250ms, and 1 object being pushed in 250ms, the reward is 0.75.

EXPERIMENTS

We conducted experiments using a distributed key-value store totally replicated across 24 replicas in 8 geographic regions on 5 continents around the world as shown in Figure 1. Replicas were hosted using AWS EC2 t2.micro instances and were connected to each other via internal VPCs when in the same region, using external connections between regions. The store, called Honu, is implemented in Go 1.9 using gRPC and protocol buffers for RPC requests; all code is open source and available on GitHub.

The workload on the system was generated by 8 clients, one in each region and colocated with one of the replicas. Clients continuously created Put requests for random keys with a unique prefix per-region (consistency conflicts only occur within a region). The average throughput generated per-client was 5620.4 puts/second. Because the mean round trip latency between each region ranged from 23ms to 600ms and synchronization requires at least two round trips, the anti-entropy delay for these experiments was set to 1 second. To account for lag between commands sent to replicas in different regions, the experiment was run for 10 minutes, the workload running for 8 minutes, offset by one minute from the start.

Our first experiments compared uniform random peer selection with epsilon greedy bandits using $\epsilon \in \{0.1, 0.2, 0.5\}$ as well as an annealing greedy epsilon bandit. The total system rewards as a rolling mean over a time window of 15 synchronizations are shown in Figure 2. The rewards ramp up from zero as the clients come online and start creating work to be synchronized. All of the bandit algorithms improve over the baseline of uniform selection, not only generating more total reward across the system, but also introducing less variability with lower ϵ values. None of the bandit curves immediately produces high rewards as they explore the reward space; lower ϵ values may cause exploitation of incorrect arms, while higher ϵ values take longer to find optimal topologies.

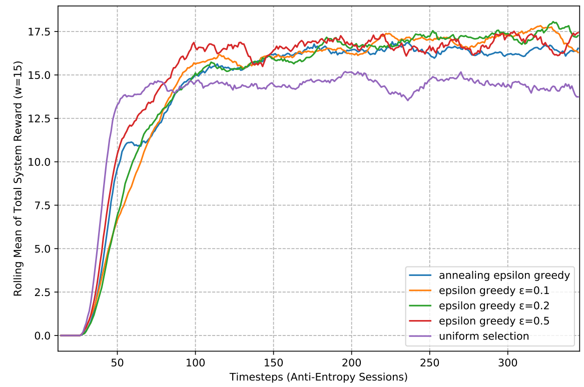

Figure 2: Total system rewards over time

We have visualized the resulting topologies as network diagrams in Figure 3 (uniform selection), Figure 4 (epsilon greedy $\epsilon = 0.1$), Figure 5 (epsilon greedy $\epsilon = 0.2$), and Figure 6 (annealing epsilon). Each network diagram shows each replica as a vertex, colored by region e.g. purple is California, light blue is Sao Paulo, Brazil. Each vertex is also labeled with the 2-character UN country or US state abbreviation as well as the replica's precedence id. The size of the vertex represents the number of `Put` requests that replica received over the course of the experiment; larger vertices represent replicas that were colocated with workload generators. Each edge between vertices represents the total number of successful synchronizations, the darker and thicker the edge is, the more synchronizations occurred between the two replicas. Edges are directed, the source of the edge is the replica that initiated anti-entropy with the target of the edge.

Comparing the resulting networks, it is easy to see that more defined topologies result from the bandit-based approaches. The uniform selection network is simply a hairball of connections with a limited number of synchronizations. Clear optimal connections have emerged with the bandit strategies, dark lines represent extremely successful synchronization connections between replicas, while light lines represent synchronization pairs that are selected less frequently. We posit that fewer edges in the graph represents a more stable network; the fewer synchronization pairs that are selected, the less noise that occurs from selecting a peer that is in a similar state.

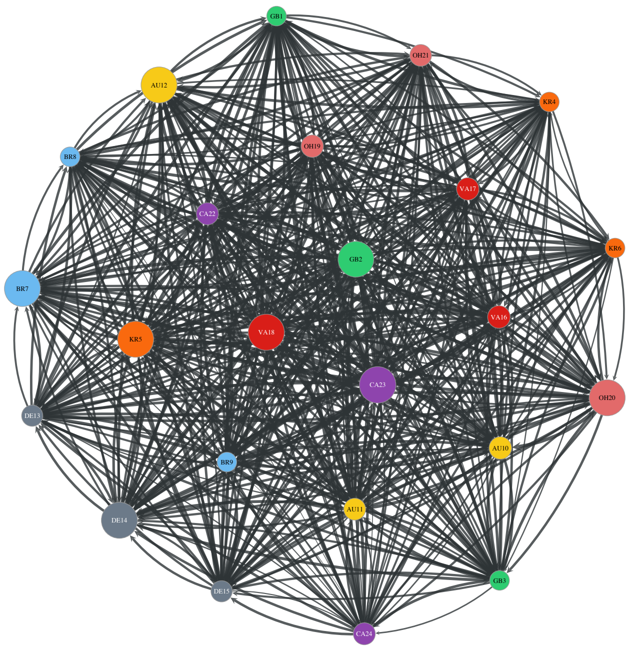

Figure 3: Uniform Selection

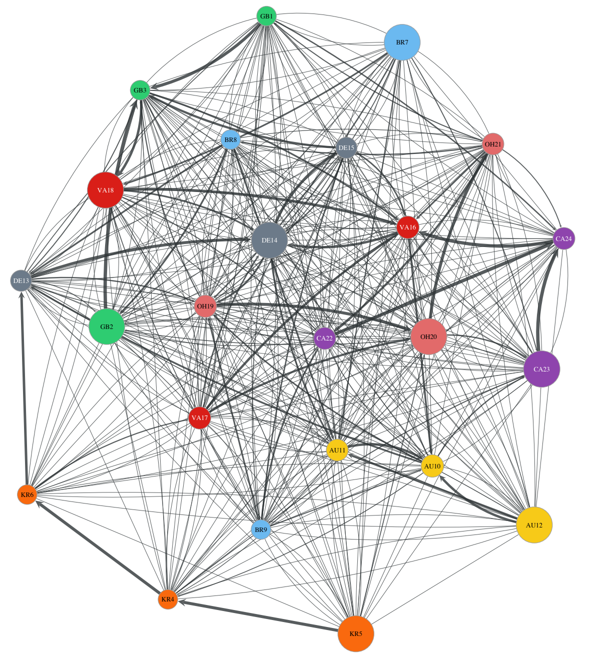

Figure 4: Epsilon Greedy $\epsilon = 0.1$

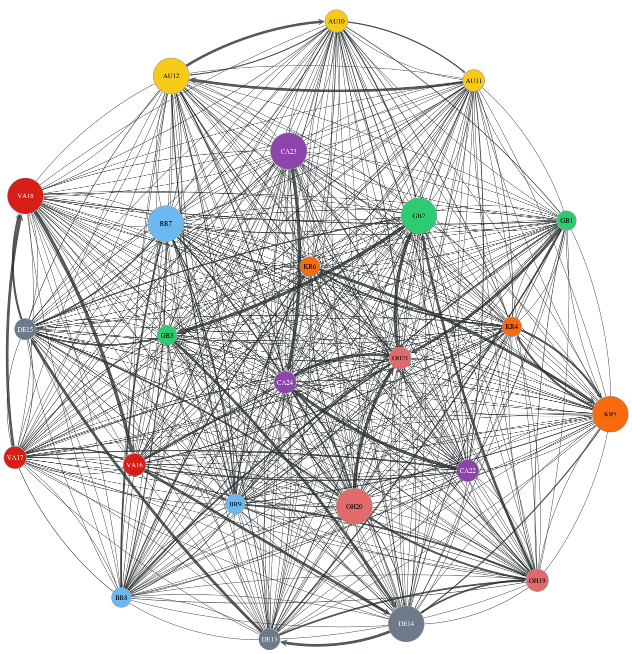

Figure 5: Epsilon Greedy $\epsilon = 0.2$

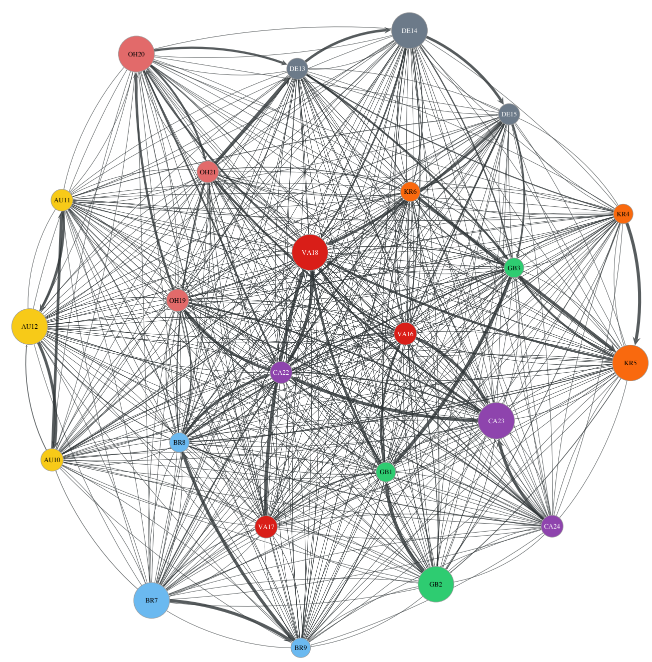

Figure 6: Annealing Epsilon

DISCUSSION

To achieve stronger eventual consistency, the visibility latency of a system replicated with anti-entropy must be reduced. We believe that this can be achieved with two primary goals: increasing the number of successful synchronizations and maximizing the the number of local and regional synchronizations such that the average latency of anti-entropy sessions is as low as possible. These goals must also be tempered against other requirements, such as fault and partition tolerance, a deterministic anti-entropy solution that ensures the system will become consistent eventually, and load balancing the synchronization workload evenly across all replicas.

Bandit based approaches to peer selection clearly reduce noise inherent in uniform random selection as shown in Figure 2, the bandit algorithms achieve better rewards over time because peers are selected that are more likely to have an update to synchronize. Moreover, based on the network diagrams shown in Figures 3-6, this is not the result of one or two replicas becoming primary syncs: most replicas have only one or two dark in-edges meaning that most replicas are only the most valuable peers for one or two other replicas. At the same time, the rewards using a bandit approach, while clearly better than the uniform case, are not significantly better. Future work to explore the reward function in detail may help to adjust the reward curves more significantly. Additionally the inclusion of penalties (negative rewards) might also make the system faster to adjust to a high quality topology. Future work must also show an increase in consistency by demonstrating a reduced number of stale reads and forked writes.

As for localization, there does appear to be a natural inclination for replicas that are geographically proximate to be a more likely selection. In Figure 5, replicas in Seoul (orange), Virginia (red), Sydney (yellow), California (purple), and Frankfurt (grey) all prioritize local connections. Regionally, this same figure shows strong links such as those between Ohio and California (`OH21` → `CA24`) or Frankfurt and London (`GB3` → `DE14`). Replicas such as `OH21` and `DE14` appear to be hubs that specialize in cross-region collaboration. Unfortunately there does also seem to be an isolating effect, for example Sydney (yellow) appears to have no significant out of region synchronization partners. Multi-stage bandits might be used to create a tiered reward system to specifically adjust the selection of local, regional, and global peers. Other strategies such as upper confidence bounds, softmax, or Bayesian selection may also create more robust localization.

Finally, and perhaps most significantly, the experiments conducted in this paper were on a static workload; future work must explore dynamic workloads with changing access patterns to more closely simulate real world scenarios. While bandit algorithms are considered online algorithms that do respond to changing conditions, the epsilon greedy strategy can be slow to change since it prefers to exploit high-value arms. Contextual bandits use side information in addition to rewards to make selection decisions, and there is current research in exploring contextual bandits in dynamic worlds that may be applicable. Other strategies such as periodic reseting of the values may incur a small cost to explore the best anti-entropy topology, but could respond to changing access patterns or conditions in a meaningful way.

CONCLUSION

In this paper we have presented a novel approach to peer selection during anti-entropy by replacing uniform random selection with multi-armed bandits. Multi-armed bandits consider the historical reward obtained from synchronization with a peer, defined by the number of objects synchronized and the latency of synchronization, when making a selection. Bandits balance the exploitation of a known high-value synchronization peer with the exploration of possibly better peers or the impact of failures or partitions. The end result is a replication network that is not only unperturbed by noise due to randomness, but also capable of more efficiently propagating updates.

In an eventually consistent system, efficient propagation of updates is directly tied to higher consistency. By reducing visibility latency, the likelihood of a stale read decreases, which is the primary source of inconsistency in a highly available system. We believe that the results presented show a promising start to a renewed investigation of highly available distributed storage systems in novel network environments, particularly those that span the globe. Future work will consider different reward functions and how the priorities of system designers can be embedded into rewards. We will also explore dynamic environments and how reinforcement learning algorithms can maintain optimal replication behavior, exploring other strategies for selection such as upper confidence bounds, softmax, or Bayesian approaches.

All code for the key-value store and bandit-based entropy as well as experimental results is open source and available on GitHub at https://github.com/bbengfort/honu.

REFERENCES

[1] Paulo SÃľrgio Almeida, Carlos Baquero, and Victor Fonte. [n. d.]. Version stamps-decentralized version vectors. In *Distributed Computing Systems, 2002. Proceedings. 22nd International Conference on* (2002). IEEE, 544–551. http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1022304

[2] Peter Bailis, Shivaram Venkataraman, Michael J. Franklin, Joseph M. Hellerstein, and Ion Stoica. [n. d.]. Quantifying eventual consistency with PBS. 23, 2 ([n. d.]), 279–302. http://link.springer.com/article/10.1007/s00778-013-0330-1

[3] David Bermbach and Stefan Tai. [n. d.]. Eventual consistency: How soon is eventual? An evaluation of Amazon S3's consistency behavior. In *Proceedings of the 6th Workshop on Middleware for Service Oriented Computing* (2011). ACM, 1. http://dl.acm.org/citation.cfm?id=2093186

[4] Giuseppe DeCandia, Deniz Hastorun, Madan Jampani, Gunavardhan Kakulapati, Avinash Lakshman, Alex Pilchin, Swaminathan Sivasubramanian, Peter Vosshall, and Werner Vogels. [n. d.]. Dynamo: amazon's highly available key-value store. In *ACM SIGOPS Operating Systems Review* (2007), Vol. 41. ACM, 205–220. http://dl.acm.org/citation.cfm?id=1294281

[5] Bernhard Haeupler. [n. d.]. Simple, fast and deterministic gossip and rumor spreading. 62, 6 ([n. d.]), 47. http://dl.acm.org/citation.cfm?id=2767126

[6] Richard Karp, Christian Schindelhauer, Scott Shenker, and Berthold Vocking. [n. d.]. Randomized rumor spreading. In *Foundations of Computer Science, 2000. Proceedings. 41st Annual Symposium on* (2000). IEEE, 565–574. http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=892324

[7] John Langford and Tong Zhang. [n. d.]. The Epoch-Greedy Algorithm for Multi-Armed Bandits with Side Information. In *Advances in Neural Information Processing Systems* (2008). 817–824. bibtex: langford_epoch-greedy_2008.

[8] Haipeng Luo, Alekh Agarwal, and John Langford. [n. d.]. Efficient Contextual Bandits in Non-stationary Worlds. ([n. d.]).

[9] Yamir Moreno, Maziar Nekovee, and Amalio F. Pacheco. [n. d.]. Dynamics of rumor spreading in complex networks. 69, 6 ([n. d.]), 066130. http://journals.aps.org/pre/abstract/10.1103/PhysRevE.69.066130

[10] Douglas B. Terry, Alan J. Demers, Karin Petersen, Mike J. Spreitzer, Marvin M. Theimer, and Brent B. Welch. [n. d.]. Session guarantees for weakly consistent replicated data. In *Parallel and Distributed Information Systems, 1994., Proceedings of the Third International Conference on* (1994). IEEE, 140–149. http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=331722

[11] Hiroshi Wada, Alan Fekete, Liang Zhao, Kevin Lee, and Anna Liu. [n. d.]. Data Consistency Properties and the Trade-offs in Commercial Cloud Storage: the Consumers' Perspective.. In *CIDR* (2011), Vol. 11. 134–143.